Flood Net: Predicting Flooded and Non-flooded Regions Using Deep Convolutional Neural Network

Mohammad Jubair Pantho
Department of Computer Science and Engineering
University of Tennessee - Chattanooga
Chattanooga, TN
wzs444@mocs.utc.edu

Kyle Ford
Department of Computer Science and Engineering
University of Tennessee - Chattanooga
Chattanooga, TN
hqz794@mocs.utc.edu

J.M. Imtinan Uddin
Department of Computer Science and Engineering
University of Tennessee - Chattanooga
Chattanooga, TN
cbj988@mocs.utc.edu

***Abstract*—Flooding is a persistent and significant issue worldwide, particularly in developing countries, where it often results in the loss of thousands of lives each year. Governments and other authorities must take steps to prevent and mitigate the damage caused by floods. However, predicting which regions will likely be affected by flooding can be challenging. In this study, we propose a neural network-based model for predicting flooded and non-flooded regions. This model leverages the power of deep learning to process and analyze large amounts of data in real-time. It uses various image features extracted by the neural network to predict flooded and non-flooded areas accurately. By training this model on testing data, we were able to achieve an accuracy of 86.81 % in predicting flooded and non-flooded regions. The results of this study are significant because they demonstrate the potential for neural network-based models to be used as a tool to help governments and other authorities better predict and prepare for flooding. This model can help inform decision-making around disaster response, emergency planning, and infrastructure development by identifying areas that are most at risk of flooding. Overall, we believe this research represents a valuable contribution to the ongoing efforts to mitigate the devastating effects of flooding on communities worldwide.**

***Index Terms*—Flooding, neural network, flood region, non flooded region**

I. Motivation

This study was motivated by the devastating impact of floods on communities around the world. Every year, thousands of lives are lost, and millions of people are displaced due to floods. Governments and humanitarian organizations are constantly seeking ways to improve flood response and prevention efforts. In this context, the development of a predictive model to identify flooded and non-flooded regions can provide critical information to support emergency response and planning efforts. The potential impact of such a model on reducing the human and economic toll of floods makes it a compelling area of research. This project aims to contribute to this important area of study and provide a practical tool that can be used to help prevent and mitigate the effects of floods. This technique can be incorporated to satellite, drone, mobile tower and high rise building that can be helpful for predicting flooded and non flooded region.

II. Introduction

Flooding is one of the immensely devastating natural events that cause severe damage and loss of life worldwide every year. [4] Every year, many people die due to unexpected flooding events. [5] In the US, natural disasters take much life causing damage to structures and turmoiling the life of people. According to a report published by the NOAA National Centers for Environmental Information (NCEI), 18 catastrophic events in the United States caused $165.0 billion, and every event, including the flooding in Missouri and Kentucky, caused economic damage to about $1.0 billion. [7] Flooding is considered a devastating natural incident. Heavy rainfall over a short period or continuous rainfall for several days is the major reason behind flooding. Sometimes the melting of ice can cause flash floods. Another major reason behind flooding is the inappropriate water flow from a dam built upstream. Bangladesh, a country in South Asia, faces rapid flooding every year due to the Farakka Dam built upstream on the Indian side. [6] In 2022, hurricane Ian caused a lot of damage and inundation of mass areas comprising a total loss of $112.9 billion and a loss of 152 lives. [7]

Using satellite imageries to classify flooding zone has been in practice for decades. [8] The flood maps are classified using images captured by satellites, Unmanned Ariel Vehicles(UAVs), and aircraft. However, images from the satellites are not significantly high in resolution, and the longer altitude reduces the clarity of the pixels of the features. [9] Recently, the boom of UAVs made data availability, reliability, and quality far easier than before. [10] UAVs are handy in practice, and due to their ability to fly in lower elevations and low operational cost, it is getting more popular in geographic analysis. Moreover, it generates images in higher resolution than satellites, which helps the models to learn features efficiently. [11]

This article uses a Convolutional Neural Network to extract features from the images captured by the DJI Mavic Pro Quadcopter. The architecture can be referred to as a tiny VGG net where two Convolutional blocks and a fully connected network extract the features. The model is trained on 2343 high-resolution images of flooding and non-flooding regions. The model can correctly classify flooding regions with 86.81 % accuracy.

III. Data

The data used to train and test the create model comes from the Floodnet Dataset. This data set contains a total of 2,343 high resolution UAS images used for testing, training, and validation. UAS imagery is an appropriate imaging source for this study because it provides high quality images and makes use of advanced technology such as satellite and drone technology. Thus, the model is more likely to obtain accurate results because the data it is being fed is of high quality. The images used in this dataset were taken by DJI Mavic Pro Quadcopters.

With regards to splitting the data, the dataset is organized into training, testing, and validation sets. The images are randomly shuffled such that each set is a random sample of all of the available images. The training dataset is comprised of 60% of the overall images, the testing dataset constitutes 20% of the overall images, and the remaining 20% are used for the validation dataset. Using these splits, the model is able to achieve high accuracy during both testing and training.

This model makes use of semi-supervised image classification and semi-supervised semantic segmentation. In order to achieve this, the dataset also features class names and indexes by which the data is classified. For semi-supervised image classification, the data features two classes with indexes 0 and 1. These indexes are "Flooded" and "Non-flooded" and correspond to classifying a particular image as being flooded or not. Conversely, semi-supervised semantic segmentation features more overall classes, ten in total, and is more granular about specifying different aspects of the image. These indexes, numbered 0-9, feature classes including "Background", "Building-flooded", "Building-non-flooded", "Road-flooded", "Road-non-flooded", "Water", "Tree", "Vehicle", "Pool", and "Grass". Through the use of these labels the model is able to identify and classify individual semantic elements found in the images rather than just classifying the image as flooded or non-flooded.

While the use of this dataset is relevant and applicable for the task discussed in this paper, it is important to realize the limitations of the dataset with regards to practical application of the model. This model is trained on 2,343 satellite images taken from DJI Mavic Pro Quadcopters. One area for further study is to expand the overall set of images processed by the model such that real-time satellite imaging can be used. While high accuracy is obtained using this particular dataset, a more applicable and practically useful dataset would include real-time satellite images. Such a dataset would help in aiding critical response units and environmental disaster units in their efforts to alleviate the effects of flooding in flooded areas. Adaptation to such a dataset would be easily implemented using the model at hand and involve the same image normalization and resizing techniques utilized in the data preprocessing stage. Thus, we believe that this model is easily adaptable to handle real-time satellite imagery as inputs, while still maintaining outstanding accuracy results.

IV. Research Methodology

The authors of this study presented an approach for predicting redicting Flooded and Non-flooded Regions Using Deep Convolutional Neural Network. The approach comprises three main components: 1) Data Collection, 2) the cleaning and preprocessing of the collected data, and 3) the training and testing of a neural network model. The proposed system's workflow is depicted in Figure 1. The important steps of our research methodology is described in the later subsection.

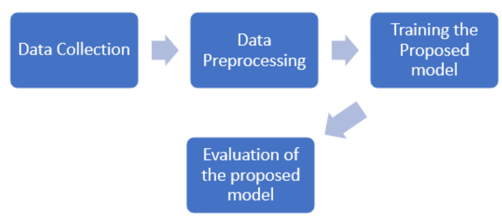

Fig. 1. Our proposed method

A. Data Preprocessing

Data preprocessing is a critical step in image classification, as it plays a significant role in ensuring the accuracy and performance of the model. Raw image data can be large, and complex and contain noise, artifacts, or variations in lighting or color that can hinder the model's performance. Data preprocessing techniques such as image resizing, normalization, augmentation, and feature extraction can help to address these issues and prepare the data for analysis. Image preprocessing can also involve removing unwanted objects or backgrounds from the images, correcting for perspective or orientation, and enhancing contrast or sharpness. Proper data preprocessing can lead to better feature representations and more accurate classification results. The quality and effectiveness of the preprocessing techniques used can significantly impact the model's performance, making it an essential step in image classification. For this reason, we have performed data preprocessing on our dataset in our proposed method. First, we have divided our dataset into training and testing sets for data preprocessing. After diving into the training and testing set, we resized our images into 28 by 28. For training a neural network, it is crucial to have all the images in the same shape; otherwise, we will not be able to train our neural network. After reshaping our images into the same shape, we loaded our training and testing dataset into a data loader where the batch size was 32. Batch size is a crucial hyperparameter in machine learning that determines the number of training samples processed in a single iteration during training. It is critical in optimizing memory usage, computational efficiency, and gradient estimation. The choice of batch size can impact regularization and generalization. Using a larger batch size can provide more accurate gradient estimates and lead to better generalization but also slow down convergence. In contrast, a smaller batch size can reduce memory usage, provide a more diverse example during training, and help prevent overfitting. Choosing an appropriate batch size requires carefully considering the available resources, the problem domain, and the model architecture. That is why we have chosen 32 as batch size, as it is more optimal for our model. Also, we have divided each dataset into two subfolders: flooded and non-flooded. From this data loader automatically labels or training and testing dataset. Figure 2 depicts the visualization of our dataset.

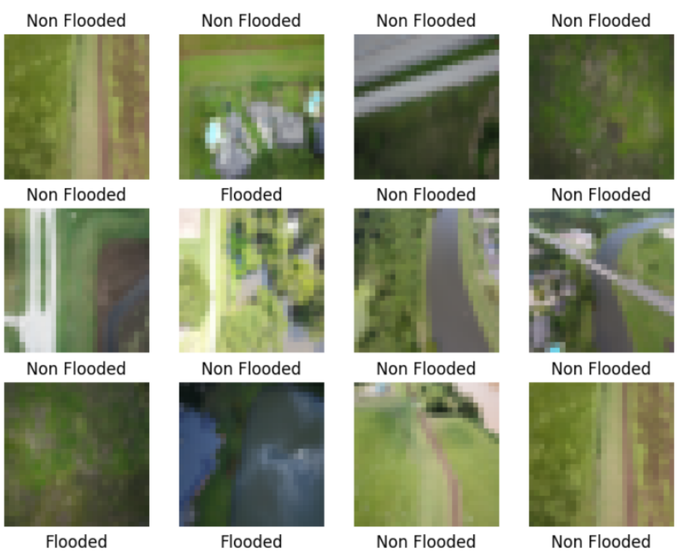

Fig. 2. visualization of our dataset

B. Model Architecture

After performing data preprocessing, we designed our model. One must be cautious about choosing a model because model results depend on the model's architecture. Figure 2 depicts the architecture of our model.

Our model has two blocks. Each block has two convolutional layers followed by a max pool layer. Also, each convolutional layer is followed by an activation function. In our model activation function is ReLU. Convolutional Neural Networks (CNNs) are a popular type of neural network used for image and video recognition. The basic building blocks of a CNN are convolutional layers, ReLU activation functions, and max pooling layers. Convolutional layers are the core of CNN architecture. They perform convolution operations on

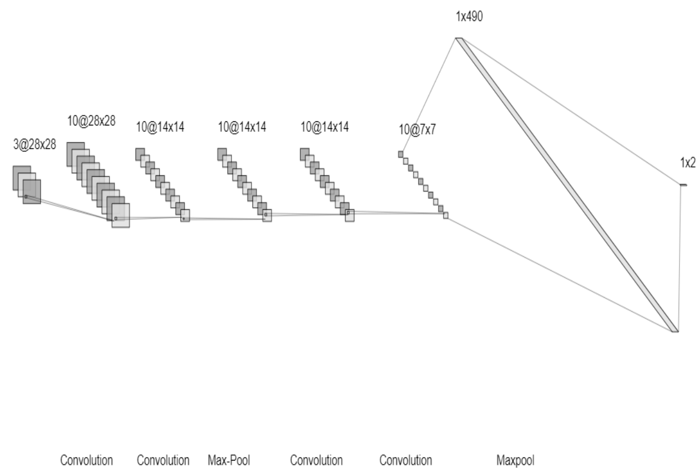

Fig. 3. Architecture of our model

the input image, where a filter or kernel is slid across to extract features. The filter weights are learned during training, and multiple filters can be used in each convolutional layer to capture different features. Convolutional layers enable the network to learn complex spatial patterns and relationships in the input image.ReLU (Rectified Linear Unit) activation functions are typically applied after each convolutional layer. ReLU functions help introduce non-linearity to the network, which allows it to learn more complex features and decision boundaries. ReLU activation functions set all negative values to zero while retaining positive values. This helps to avoid the vanishing gradient problem, which can occur when gradients become too small during backpropagation. Max pooling layers are often used after convolutional and ReLU layers to reduce the feature maps' spatial size and help prevent overfitting. Max pooling operates by sliding a window over the feature map and taking the maximum value in each window. This operation reduces the spatial size of the feature maps, which can help the network generalize better to new data. Overall, these three components of a CNN - convolutional layers, ReLU activation functions, and max pooling layers - work together to extract and learn relevant features from the input image, reduce the spatial size of feature maps, and enable the network to make accurate predictions.

C. Training and Testing of the proposed model

After designing our proposed model, we trained our model and then tested the model to evaluate the results. We ran the model for 20 epochs, and the learning rate was 0.1. We have also used stochastic gradient descent and categorical cross entropy as optimization and loss algorithms. An epoch is a single pass through the entire training dataset during neural network training. Multiple epochs are typically required to train the network and fully optimize the model's performance.

The learning rate is a hyperparameter that controls the step size or rate at which the network parameters are updated during training. A larger learning rate may result in faster convergence but can also overshoot the optimal solution. A lower learning rate may take longer to converge but can provide more stable updates.

Stochastic gradient descent (SGD) is a popular optimization algorithm used to train neural networks. It updates the model parameters by computing the gradient of the loss function for the weights for each batch of training data. SGD updates the weights in the steepest descent direction, which helps minimize the loss function.

A loss function is a function that measures the difference between the predicted output of the network and the actual target values. The goal of the training process is to minimize this loss function. Standard loss functions include mean squared error (MSE) for regression tasks and categorical cross-entropy loss for classification tasks.

Categorical cross-entropy loss is a loss function used in multi-class classification tasks. It measures the dissimilarity between the predicted class probabilities and the actual class probabilities. It is calculated as the negative log-likelihood of the actual class, where the predicted probability of the true class scales the log-likelihood. The cross-entropy loss is used to measure how well the neural network can classify the input data.

After training our proposed model, we achieved 87.12 % training accuracy and 86.81 % testing accuracy. Figures 4 and 5 depict the visualization of our training accuracy.

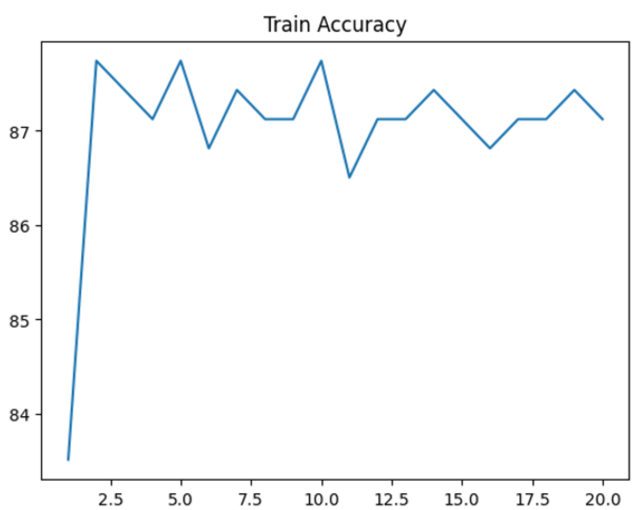

Fig. 4. Training Accuracy of our model

V. Results

This section describes the results of our proposed model. Figure 6,7 depicts the visualization of our results and confusion matrix. A confusion matrix is a table that is often used to evaluate the performance of a classification model. It shows

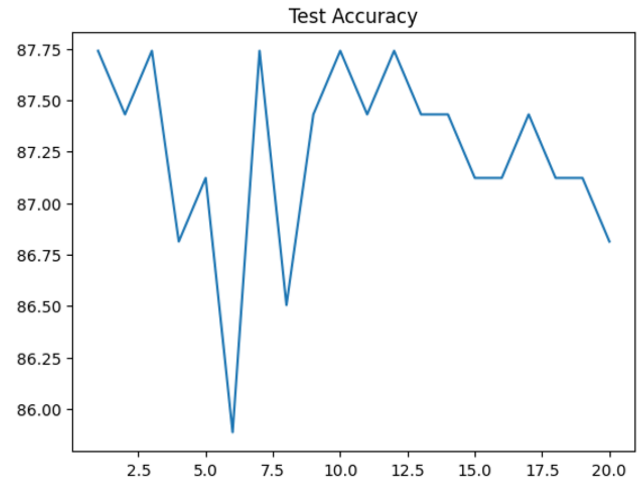

Fig. 5. Test Accuracy of our model

the number of true positive, true negative, false positive, and false negative predictions made by the model.

A confusion matrix in a binary classification problem has two rows and two columns. The rows correspond to the actual classes of the data, while the columns correspond to the predicted classes. The four cells of the matrix represent the count of each type of prediction: true positives, true negatives, false positives, and false negatives.

True positives (TP) are when the model correctly predicts the positive class. True negatives (TN) are when the model correctly predicts the negative class. False positives (FP) are when the model predicts the positive class, but the actual class is negative. False negatives (FN) are the cases when the model predicts the negative class, but the actual class is positive.

The values in the confusion matrix can be used to calculate various performance metrics for the classification model, such as accuracy, precision, recall, and F1-score. The confusion matrix provides a comprehensive view of how well the model performs and can help identify areas where the model may need improvement.

VI. Discussion

In addition to the model presented in this paper, there are a number of similar models found in the literature that perform similar tasks. A comparison of a sample of these models is presented now in an effort to illustrate the efficacy of the model presented. First, [3] presents a classification model similar to the one presented in this paper. This model is designed to classify satellite images as being flooded or non-flooded. In this regard, it accomplishes the same basic feature. Structurally, the model is similar in its design as it makes use of multiple convolutional layers. The input to this particular model is individual RGB pixels, normalized to size 11 * 11 * 4. This model utilizes three convolution layers. The first two convolution layers are followed by ReLU activation functions, and the third is followed by a softmax regression function

Fig. 6. Test results of our model

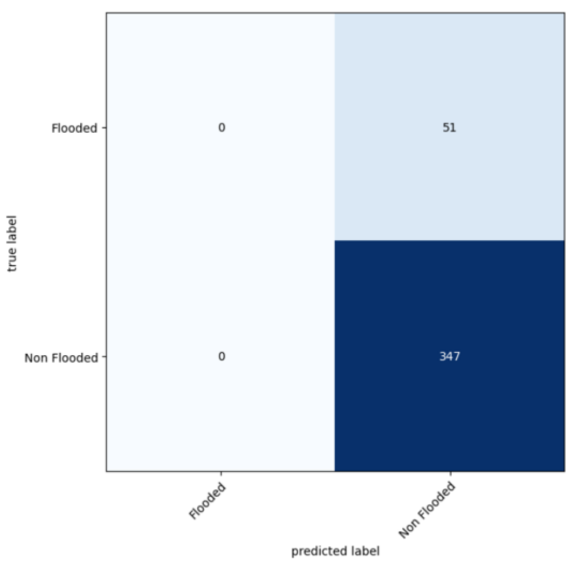

Fig. 7. Confusion Matrix of our proposed model

[3]. The processed image is then passed through a logistic regression layer, the output of which is a probability map for each of the three classes. These three maps are recombined to produce the output image with each pixel labeled according to the highest probability class that it belongs to [3]. A diagram of the architecture is given below.

In terms of results, this model achieves testing accuracy between 84% and 94%, depending on how the values of the learnable parameters are tuned [3]. This is about in line with the testing accuracy of the model presented in this paper. For reference, this model obtained 87% testing accuracy.

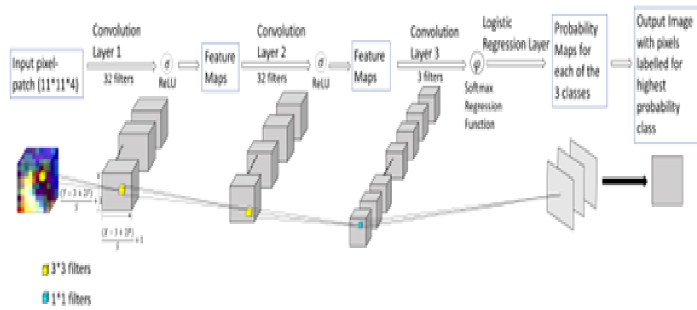

Fig. 8. Convolutional Neural Network With Logistic Regression Layer

The second model surveyed for the purposes of comparison measures the depth of flooding by processing street signs [1]. This represents a slightly different problem than the problem our model attempted to solve. Rather than accomplishing a pure classification task, this model classifies and identifies flood water depth. This model provides useful insight into possible expansion of the presented model. One area of future research is enabling our model to identify the specific area of flooded regions in satellite imaging in order to identify a specific, isolated geographic region that is flooded. [1] accomplishes its task through the use of a convolutional layer followed by a fully connected layer [1]. The purpose of the convolutional layer is to classify aspects of an RGB image as either a stop sign or not a stop sign. Once a stop sign has been identified, the fully connected layer is used to map the distance from the stop sign to the ground. In this way, the model is able to compute the approximate depth of flood water in flooded regions.

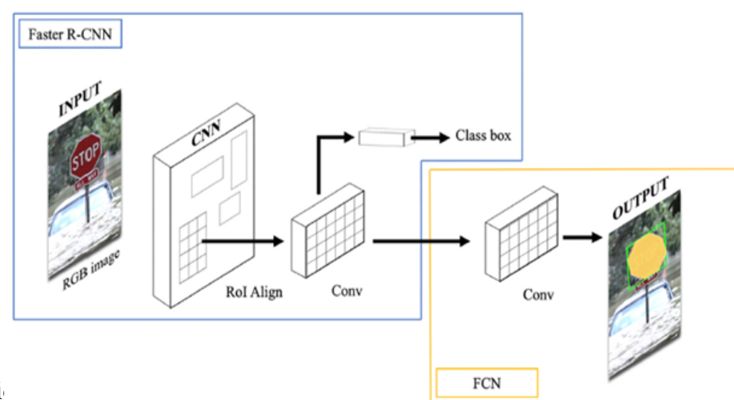

Fig. 9. Flood Depth Mapping Using Street Images

In terms of results, this model achieved an RMSE of 17.43 and 8.61 in pre- and post-flood phots and obtained an MAE of 12.63 in flood water depth estimation. This model serves as a base point for future research regarding our model.

[2] presents another model useful in aiding future research regarding our model. Specifically, it develops a model measuring the extent of flooded regions. This is another model that

provides a framework for future research regarding the model we present. Specifically, this model performs classification based on different classes in an effort to identify flooded regions. One pertinent class that is identified is the water class, and the total area of pixels classified under this class represents the extent of flooding in a given image [2]. In its current form, our model performs pure classification, classifying satellite images as flooded or non-flooded. One area for future research that has been identified is using semi-segmented classification to classify specific elements in the images to calculate the area of flooded regions. This area would correspond to a geographic region that is flooded. This model utilizes a classic VGG16 architecture [2]. Under this architecture, RGB images are passes through a single max pooling layer and then through multiple convolutional layers. Each convolutional layer is followed by a ReLU activation function. At the conclusion of the convolutional layers is three fully connected layers, each of which is followed by a ReLU activation function. The final component of the model is a softmax activation function, which transforms individual image elements into probabilities that that element belongs to a specific class. A diagram of the bVGG-16 architecture is given below.

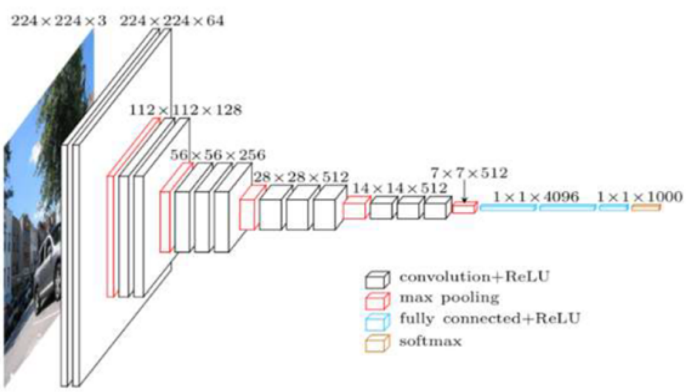

Fig. 10. VGG-16 Architecture

This model uses these probabilities to classify image elements as water or not water. In this way, the model is able to identify specific regions that are flooded and use this classification to identify the extent of flooding. In sum, this model obtains 97.52% test accuracy in extracting flooded area or water class [2].

With regards to our model, we find that we obtain similar results to other models surveyed. [3] describes a model that classifies flooding using a convolutional neural network. Depending on the values of the learnable parameters inherent to the model, the model achieves a test accuracy ranging from 84% and 95%. This is within the test accuracy range that our model achieved, with our model measuring at 87%. Furthermore, this model most closely replicated the functionality that our model did. Both are pure classification models meant to identify flooding in an overall image. With this in mind, it is worth noting that both models perform similarly in terms of test accuracy. However, while these models are similar, it is worth noting their differences. [3] makes use of three convolutional blocks to achieve its results, while our model makes use of two. Additionally, our model utilizes multiple max pooling layers to further classify the results. Moreover, [3] makes use of a logistic regression layer, while ours uses a fully connected linear layer. The difference in these two methodologies points back to the difference in purpose for the models. Recall that [3] takes as input pixel information for an RGB image, while our model takes in an RGB image normalized to 28 * 28 * 3. Because [3] is attempting to classify pixel information, a logistic regression layer is more appropriate for determining the probabilities of that pixel belonging to a particular class. Conversely, our model utilizes a fully connected layer in order to classify the image as a whole. It is worth noting that while both models utilize different methodologies to obtain their results, they perform similarly in terms of testing accuracy.

Both [1] and [2] help identify areas for future research and potential improvement of the model. In its current state, the model is useful for classification tasks. However, with some fine tuning, this model can be further improved to perform additional tasks, including those described by [1] and [2]. Specifically, future research should be focused on allowing the model to identify the area of a flooded region such that it can be mapped to a specific geographic region. Our model allows for classification of satellite images as either flooded or non-flooded. While the model is useful and has been proven to be accurate at that task, it does not mean that every pixel in the image is part of the flooded region. With the appropriate tuning of the model, we believe that the model can be altered such that it measures the area of the flooded region. Subsequently, this area could be mapped to a specific geographic region on a map. Altering the model in such a way would be useful as it would allow for emergency and disaster response teams to be more targeted and efficient in their responses. Also, it would allow for public services to better aid the public in avoiding and evacuating flooded areas in an effort to minimize the damages of flooding. We believe that this goal can be accomplished using semi-segmented classification, where image elements are classified according to specific classes. These classes would further segment the image into flooded and non-flooded regions, from which an area could be calculated. This area would then be mapped to latitude and longitude points to define a specific geography that is experiencing flooding at a given point in time.

Finally, further research using real-time satellite images would provide another source by which the model could be improved. This data allows the model to operate in real-time, minimizing in delays in identifying flooded regions, and therefore maximizing the efficiency by which emergency response teams and public services and be deployed.

VII. Conclusion

In conclusion, we present a deep neural network with the goal of predicting flooded and non-flooded regions in satellite imagery. This model can be used in the event of natural disaster, allowing response teams to respond to flooding in a more efficient fashion. Additionally, one goal of the model is to identify efficient hazard areas, which further aid in this stated goal. The ability to identify flooding in a particular geographic region is the first step in deploying any emergency response to mitigate the damage of the flooding. The use of satellite imagery to identify these flooded regions has been around for a long time. This paper presents an improved model aimed at more efficiently identifying these areas. We present a model that can help improve the response in the event of natural disaster caused by flooding.

The data this model is trained and tested on includes 2,343 high resolution UAS images taken by DJI Mavic Pro Quadcopters. These images provide a high-quality data source by which the model is tested. We use a 60%/20%/20% train/test/validation split. Each image is processed using the RGB scale and normalized to 28 * 28 * 3. The model features a deep convolutional neural network in which two consecutive convolutional layers are followed by a max pooling layer. ReLU is used as the activation function following the convolutional layers. In total, four convolutional layers and two max pooling layers are used, followed by a fully connected layer to produce the output image, which is classified as flooded or non-flooded. In this way, the model can be classified as a mini VGG model. A traditional VGG model features more convolutional and max pooling layers, and is thus a deeper model. We find that we achieve excellent results without employing the computational overhead involved in a full VGG model. Thus, a mini VGG model is both more compact and highly efficient in accomplishing the stated goal.

This model achieves both training and testing accuracy of 87%. We find these results are adequate and comparable to similar models found in the literature. Similar models using classification techniques feature test accuracy ranging from 84% to 97% depending on the values of learnable parameters. We find that this model is efficient in accomplishing its stated task in flood classification. Other models surveyed for the purpose of comparison illustrate areas for future research. The first surveyed model involves mapping the depth of flood-water depth using street images, specifically stop signs. This feature would be useful in assessing the extent of flooding, thus giving emergency response units an idea of how bad the situation is in order to deploy a proportional response. The second model studied used a full VGG-16 architecture to map the extent of flood waters in a given image. Both of these models provide useful insight in furthering our research and adapting our presented model for other applications. We identify that further research should be focused on identifying specific flooded areas that can be mapped to geographic regions and using real-time satellite images. The ability to map flooded areas in the images to real geographical locations allows for a more precise response. Second, the use of real-time images can help improve the response time of emergency response teams in assisting in these flooded areas. Both of these are primary topics identified and should be the focus of future research.

VIII. Future Works

The present study has introduced a neural network model that has shown promising results in predicting flooded and non-flooded regions. This work opens up varius avenues for future research. One possible direction would be to extend the model to different regions and test its accuracy and performance in varying contexts. Additionally, augmenting the model with factors such as urbanization, land use, and population density may improve its accuracy. Further exploration into incorporating real-time data sources to enable timely predictions would also be beneficial. Moreover, integrating the model with flood response systems to provide emergency response recommendations could be a valuable addition. The boundary box could be utilized to identify the flooded region's boundaries. Additionally, alternative machine learning techniques such as decision trees, support vector machines, and random forests could be explored to compare their performance with the neural network method. These future directions have the potential to enhance the model's accuracy and usefulness, resulting in more effective flood prevention and response initiatives.

IX. Acknowledgement

We express our gratitude to Dr. Yu Liang for providing continuous guidance and encouragement throughout the duration of this project. Without his unwavering support, this study would not have been possible. Additionally, we would like to extend our appreciation to the team members who worked tirelessly to ensure the success of this project. Their hard work and dedication have been instrumental in achieving our objectives. Together, we have achieved a significant milestone and we look forward to continued collaboration on future projects.

References

[1] Alizadeh Kharazi, B., Behzadan, A. H. (2021). Flood depth mapping in street photos with image processing and deep neural networks. Computers, Environment and Urban Systems, 88, 101628. https://doi.org/10.1016/j.compenvurbsys.2021.101628

[2] Gebrehiwot, A., Hashemi-Beni, L., Thompson, G., Kordjamshidi, P., Langan, T. (2019). Deep convolutional neural network for flood extent mapping using unmanned aerial vehicles data. Sensors, 19(7), 1486. https://doi.org/10.3390/s19071486

[3] Sarker, C., Mejias, L., Maire, F., Woodley, A. (2019). Flood mapping with convolutional neural networks using spatio-contextual pixel information. Remote Sensing, 11(19), 2331. https://doi.org/10.3390/rs11192331

[4] Rodriguez, J.; Vos, F.; Below, R.; Guha-Sapir, D. Annual Disaster Statistical Review 2008: The Numbers and Trends; Centre for Research on the Epidemiology of Disasters (CRED): Brussels, Belgium, 2009.

[5] Jonkman, S. N. (2005). Global perspectives on loss of human life caused by floods. Natural hazards, 34(2), 151-175.

[6] Gain, A. K., Giupponi, C. (2014). Impact of the Farakka Dam on thresholds of the hydrologic flow regime in the Lower Ganges River Basin (Bangladesh). Water, 6(8), 2501-2518.

[7] 2022 U.S. billion-dollar weather and climate disasters in historical context https://www.climate.gov/news-features/blogs/2022-us-billion-dollar-weather-and-climate-disasters-historical-context

[8] Huang, X.; Wang, C.; Li, Z. A near real-time flood-mapping approach by integrating social media and post-event satellite imagery. Ann. GIS 2018, 24, 113–123.

[9] Revilla-Romero, B.; Hirpa, F.A.; Pozo, J.T.D.; Salamon, P.; Brakenridge, R.; Pappenberger, F.; De Groeve, T. On the use of global flood forecasts and satellite-derived inundation maps for flood monitoring in data-sparse regions. Remote Sens. 2015, 7, 15702–15728.
[10] Feng, Q.; Liu, J.; Gong, J. Urban flood mapping based on unmanned aerial vehicle remote sensing and random forest classifier—A case of Yuyao, China. Water 2015, 7, 1437–1455.
[11] Boccardo, P.; Chiabrando, F.; Dutto, F.; Tonolo, F.; Lingua, A. UAV deployment exercise for mapping purposes: Evaluation of emergency response applications. Sensors 2015, 15, 15717–15737.